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TIME VARIATION IN THE DYNAMICS OF WORKER FLOWS: EVIDENCE FROM THE US AND CANADA

BY

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Time Variation in the Dynamics of Worker Flows: Evidence from the US and Canada

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ABSTRACT

VAR methods have been used to model the inter-relationships between inflows and outflows into unemployment and vacancies using tools such as impulse response analysis. In order to investigate whether such impulse responses change over the course of the business cycle or or over time, this paper uses TVP-VARs for US and Canadian data. For the US, we find interesting differences between the most recent recession and earlier recessions and expansions. In particular, we find the immediate effect of a negative shock on both inflow and outflow hazards to be larger in 2008 than in earlier times. Furthermore, the effect of this shock takes longer to decay. For Canada, we find less evidence of time-variation in impulse responses.

JEL Classification: J64; J63; C32.

Keywords: unemployment hazards, labor market dynamics, time-varying parameter VAR, sign-restricted impulse responses

1 Introduction

Changes in unemployment rates depend on both flows into and out of unemployment. Understanding how unemployment is affected by both these flows has a attracted a great deal of attention in the literature. Since the seminal work of Darby, Haltiwanger and Plant (1986), many studies have used descriptive measures to investigate the ins and outs of unemployment (e.g. Hall, 2005, Shimer, 2007, Elsby et al, 2009, Fujita and Ramey, 2006 and 2009 and Campolieti, 2011, among many others). However, while these descriptive methods can be helpful in characterizing the flows into and out of unemployment as well as changes in unemployment rates, they do not take into account dynamics so they miss some aspects of the adjustment process in the labor market. Arguing that descriptive measures may not be useful in disentangling shocks generated out of the labor market, such as productivity shocks, from those generated within the job search/matching system, Fujita (2011) uses VAR models to explore the interrelationships between the ins and outs of unemployment and vacancy rates in the US. He identifies the structural VAR structure using the sign restriction approach of Uhlig (2005). In particular, he identifies a negative aggregate shock as one which causes changes to unemployment to be negative for k quarters and does not immediately raise vacancies. This is the framework on which we build in the present paper.

The analysis of Fujita (2011) is conducted using a VAR with constant coefficients and, thus, impulse responses which are also constant. This can be potentially misleading if the mechanisms underlying the job search/matching process are varying over time. Results of many studies (e.g. Hall 2005, Shimer 2007, Elsby et al, 2009) suggest that the dynamics of the ins and outs of unemployment can be closely related to the fluctuations of business cycles. In the time series literature, many empirical papers (for example, Koop and Potter, 1999 and Skalin and Teräsvirta, 2002) find considerable evidence of nonlinearities in unemployment. To take account of these possible nonlinear effects, this paper extends Fujita (2011) by using a time-varying parameter (TVP) VAR. We adopt the TVP-VAR of Primiceri (2005) which additionally allows for multivariate stochastic volatility and is popular in the empirical macroeconomics literature. This framework is attractive since it allows both the VAR coefficients and the error covariance matrix to vary over time in a flexible and unrestricted fashion.

We estimate VARs and TVP-VARs using three series: the inflow hazard (job separation rate); the outflow hazard (job finding rate); and, vacancies. We use both Canadian and US data. Our empirical results provide support for the TVP-VAR with multivariate stochastic volatility. This support is particularly strong for the US data. We also find support for the inequality restrictions we use to identify the impulse responses. These lead to uniformly sensible responses to a shock for all the series we consider for both the US and Canada. In particular, we find that the inflow hazard (separation rate) increases quickly after a shock before declining slowly. In contrast, the outflow hazard (job finding rate) and vacancies decrease after a shock before increasing in a hump shaped pattern. This general pattern holds for both the US and Canada. The only slight difference between the countries is that the impulse responses for Canada tend to oscillate a bit before decaying in some cases. We do not find much evidence of time variation in impulse responses using Canadian data. However, we find some interesting time variation in the US data. While the impulse responses for most of the time periods we consider are similar, the impulse responses for the inflow and outflow hazard in the US Great Recession differ from earlier periods. In particular, the inflow hazard tends to respond more strongly to a shock and takes longer to dissipate. Furthermore, the outflow hazard also responds more strongly initially and takes longer to decay and is still quite large at the end of the time horizon we consider. These findings tend to be consistent with the observations made by Elsby et al (2010a) on the US labor market during the Great Recession.

2 Econometric Methods

VAR methods have enjoyed wide popularity in empirical macroeconomics since the pioneering work of Sims (1980). VARs are atheoretical models which allow the researcher to investigate the relationships between time series variables without imposing any economic theory. Structural identifying restrictions are placed on VARs in order to give an economic interpretation to impulse responses and other features of interest. Traditionally, these identifying restrictions have been equality restrictions and, in some cases, have been criticized for being overly strong. Uhlig (2005) proposes using weaker sets of inequality restrictions in order to identify impulse responses. This attempt to impose the minimum amount of economic theory used, and let the data speak, is in the spirit of the atheoretical VAR literature. These considerations presumably motivated Fujita (2011), who used a VAR involving inflow and outflow hazards and vacancy rates along with a sign restriction approach.[1] This approach required the minimal assumptions that a negative shock cannot immediately raise vacancies and cannot cause the unemployment rate to fall for k quarters.

Our econometric methods also begin with VARs with impulse responses being identified through similar sign restrictions. However, we also use TVP-VARs which allow for VAR coefficients to change over time. In empirical macroeconomics, there is a plethora of evidence of structural breaks and other kinds of

[1] Fujita (2011) also considers an expanded VAR, which includes additional shocks and restrictions, but found that both the expanded and simplier VARs produced the same sort of responses in the components of unemployment. Fujita (2011) concludes that his benchmark trivariate VAR provided a robust description of the adjustment process in the labor market.

parameter change (see, among many others, Stock and Watson, 1996) and this has led to a large number of papers which use TVP-VARs (see, among many others Cogley and Sargent, 2001, 2005, Cogley et al, 2005, Primiceri 2005, and D'Agostino et al, 2009 and Koop et al, 2009). It is also worth noting that most of these TVP-VARs paper allow for multivariate stochastic volatility which seems to be empirically important in many macroeconomic applications. One purpose of the present paper is to see whether TVP-VARs with multivariate stochastic volatility will prove equally useful in applications in labor economics.

In this section, we briefly outline the structure of TVP-VARs and describe how we implement the sign restriction approach to impulse response analysis. The Technical Appendix provides additional details. Our TVP-VAR setup follows Primiceri (2005) and the sign restriction approach is implemented as in Uhlig (2005) and the reader is referred to these papers for additional motivation and explanation.

The basic VAR used by Fujita (2011) can be written as

$$y_t = Z_t\theta + \varepsilon_t \tag{1}$$

where y_t is an $n \times 1$ vector of observations on the dependent variables, Z_t is an $n \times m$ matrix of containing a vector of intercepts and lagged dependent variables and ε_t are independent $N(0, H)$ for $t = 1, 2, ..., T$. The TVP-VAR extends this as

$$y_t = Z_t\theta_t + \varepsilon_t \tag{2}$$

where

$$\theta_t = \theta_{t-1} + \eta_t. \tag{3}$$

and η_t are independent $N(0, Q)$. Notice that this takes the form of a state space model and the time-varying VAR coefficients can be interpreted as an $m \times 1$

vector of unobserved states. This is a popular specification which allows for the coefficients to vary over time. It has the advantage that standard statistical methods for state space models exist. In our empirical work, we refer to this as the homoskedastic TVP-VAR, to distinguish it from the heteroskedastic TVP-VAR which assumes ε_t are independent $N(0, H_t)$. Following Primiceri (2005), we use a triangular decomposition to model H_t:

$$H_t = A_t^{-1}\Sigma_t\Sigma_t^{'}(A_t^{-1})^{'}, \tag{4}$$

where Σ_t is a diagonal matrix with diagonal elements $\sigma_{j,t}$ for $j = 1, 2, ..., n$ and A_t is a lower triangular matrix with ones on the diagonal. That is, it takes the form:

$$A_t = \begin{pmatrix} 1 & 0 & ... & . & 0 \\ a_{21,t} & 1 & ... & . & . \\ . & . & ... & . & . \\ . & . & ... & 1 & 0 \\ a_{n1,t} & . & ... & a_{n(n-1),t} & 1 \end{pmatrix}$$

Let $\sigma_t = (\sigma_{1,t}, \sigma_{2,t}, ..., \sigma_{n,t})'$ and $a_t = (a_{21,t}, a_{31,t}, a_{32,t}, ..., a_{n(n-1),t})'$. These are allowed to evolve according to the following state equations:

$$log(\sigma_t) = log(\sigma_{t-1}) + u_t, \tag{5}$$

and

$$a_t = a_{t-1} + v_t, \tag{6}$$

where $u_t \sim i.i.d.N(0, W)$, $v_t \sim i.i.d.N(0, C)$, and u_t and v_t are independent to each other with all the leads and lags. As discussed in Primiceri (2005), this specification is a flexible one, allowing both error variances and covariances to evolve over time.

Our empirical work considers VARs, homoskedastic TVP-VARs and heteroskedastic TVP-VARs. We use the Bayesian information criterion (BIC) to compare these models. This can be interpreted as an asymptotic approximation to the log of the marginal likelihood (the conventional Bayesian model comparison metric). Note that BIC does not involve the prior, which is potentially an advantage in high-dimensional models such as VARs and TVP-VARs where marginal likelihoods can be sensitive to prior choice. Following Carlin and Louis (2000, Section 6), we calculate the BIC using the posterior expectation of the log-likelihood.

Additional technical details, including discussion of posterior simulation and the priors used in our Bayesian estimation procedure, are given in the Technical Appendix. The reader is referred to Koop and Korobilis (2009) for complete details Bayesian estimation of VARs and TVP-VARs.

The Technical Appendix also gives details of how the sign-restricted impulse responses are calculated. We use the same methods as Uhlig (2005) and Fujita (2011). These require the specification of restrictions and we use the same restrictions as in Fujita (2011) which identify an aggregate shock using the following restrictions:

1. A negative aggregate shock will causes changes in unemployment to be non-negative for k quarters.

2. A negative aggregate shock will not raise vacancies in the impact quarter.

In line with Fujita (2011), in this paper we set $k = 2$. In the online empirical appendix, we also present results for $k = 1, 3, 4$ and find results to be fairly robust to choice of k.

Note that the first restriction relates to the unemployment rate. Following Shimer (2007) and Elsby et al (2010a), we approximate the unemployment rate

(ue_t) by the steady-state unemployment rate:

$$ue_t \approx \frac{s_t}{f_t + s_t}$$

where s_t is the inflow hazard and f_t is the outflow hazard.

We present impulse responses for the three variables in y_t (i.e. the inflow and outflow hazards and the vacancy rate) plus the unemployment rate. With regards to the latter we proceed as follows. After a shock at time t, if the responses of the inflow hazard and outflow hazard at time $t+1$ are $irf_{s,t+1}$ and $irf_{f,t+1}$, respectively, the impulse response of unemployment at time $t+1$ ($irf_{ue,t+1}$) can be approximated by the following equation:

$$irf_{ue,t+1} \approx \frac{s_t + irf_{s,t+1}}{f_t + s_t + irf_{s,t+1} + irf_{f,t+1}} - ue_t$$

Similarly, the impulse responses of unemployment for future horizons t_{hr}, which is longer than 1, can be approximated by:

$$irf_{ue,t+t_{hr}} \approx \frac{s_t + \sum_{ii=1}^{t_{hr}} irf_{s,t+ii}}{f_t + s_t + \sum_{ii=1}^{t_{hr}} (irf_{s,t+ii} + irf_{f,t+ii})} - \frac{s_t + \sum_{ii=1}^{t_{hr}-1} irf_{s,t+ii}}{f_t + s_t + \sum_{ii=1}^{t_{hr}-1} (irf_{s,t+ii} + irf_{f,t+ii})}$$

In our empirical work, we also present a variance decomposition arising from the sign-restricted impulse response approach. Defined as in Fujita (2011), this measures the proportion of the forecast error variance at different horizons which can be attributed to the identified aggregate shock.

3 Empirical Results

We divide our empirical results section into three sub-sections. The first describes the data while the second discusses modelling choices and volatility estimates. The third sub-section presents impulse responses and variance decompositions.

3.1 Data

We use quarterly data from the US and Canada. The US data runs 1951Q1-2009Q4, while the Canadian data spans 1981Q1 through 2003Q2. The shortness of the Canadian data is due to the decision of Statistics Canada to terminate the help wanted index in April, 2003.

The US data were obtained from Elsby et al (2010a) and include the inflow and outflow hazard series, which were computed using data from the Current Population Survey (CPS), as well as a help wanted index. The US help wanted index is collected by the Conference Board and is based on help wanted ads in 51 prominent newspapers in the US. The Canadian inflow and outflow hazard series were originally computed in Campolieti (2011) using the public release files of the Labour Force Survey (LFS), which is collected by Statistics Canada and is comparable to the US CPS. The help wanted index is obtained from Statistics Canada's CANSIM database.[2] The Canadian help wanted index is based on the number of job ads in newspapers and is comparable to the US help wanted index we use.[3] The inflow and outflow hazard rates for both the US and Canada are based on the framework introduced by Shimer (2007) with the refinements in Elsby et al (2009). These hazard rates measure the flows into unemployment and out of unemployment.[4] Details on the computation of the inflow hazards can be found in Elsby et al (2009), Elsby et al (2010a) and Campolieti (2011).

Figures 1 and 2 plot the raw data for the US and Canada, respectively.

[2] This help wanted index was introduced during the first quarter of 1981.

[3] There was also an earlier help wanted index that was available from 1962 to 1988. This index was proportional to the space occupied by job offers in Canada's major newspapers, but is was not a robust a measure because it was sensitive to changes in fonts and column widths as well as paper size in the newspaper industry.

[4] Fujita (2011) used inflow and outflow hazard series computed from gross flows data.

It can be seen that there is some evidence of low-frequency trends in the data. Fujita (2011) argues that theoretical search/matching models are not associated with low-frequency trends and, accordingly, takes out such low frequency trends. Following Fujita (2011), we detrend all our series using deterministic quadratic trends.

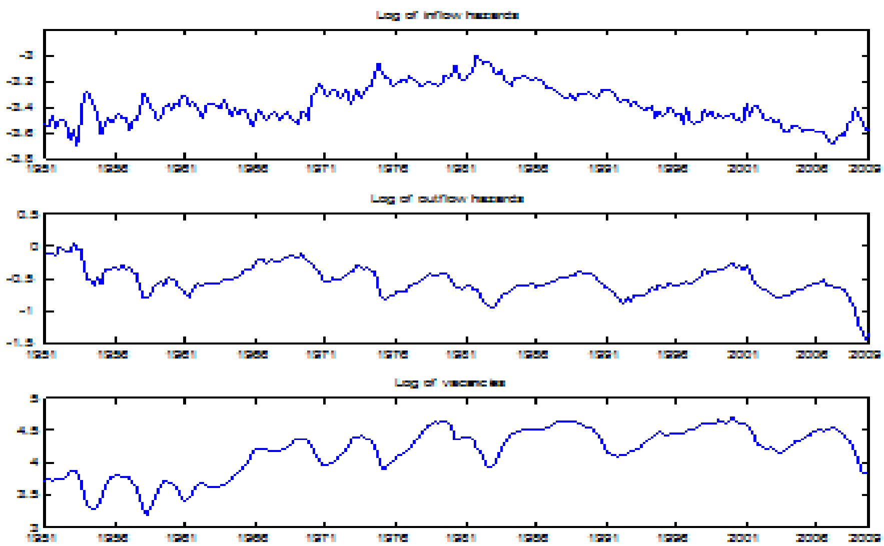

Figure 1. US data

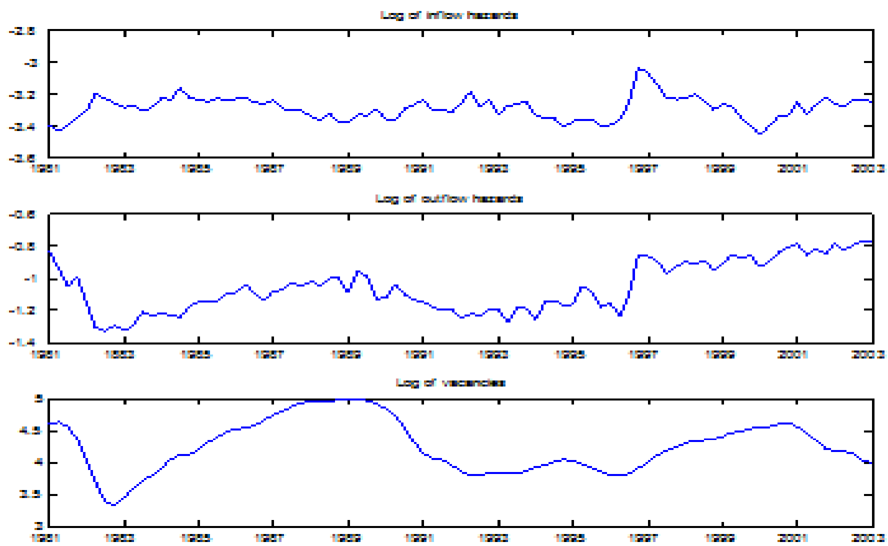

Figure 2. Canadian data

3.2 Model Comparison

BIC chooses VAR models with lag length 2 for the US and Canada and we adopt this choice for all of our VARs and TVP-VARs. With regards to the degree of time-variation in VAR coefficients and error variances, Table 1 presents BICs for three models. For notational convenience, we use 'Homo TVP-VAR' to denote TVP-VAR models with constant error covariance matrix, and 'Hete TVP-VAR' to denote TVP-VAR models with time varying error covariance matrix. Table 1 indicates moderately strong support for time-variation in both VAR coefficients and the error covariance matrix. That is, for both countries the Homo TVP-VAR has a substantially lower BIC than the VAR and the heteroskedastic TVP-VAR in turn has a substantially lower BIC than the TVP-VAR. Accordingly, in the remainder of this paper we will focus mainly on the heteroskedastic TVP-

VAR. However, a complete set of results for all models is available in the online appendix.

Table 1: BIC for Various Models		
	Canada	US
VAR	6.6504	7.5446
Homo TVP-VAR	-0.4346	-1.6442
Hete TVP-VAR	-8.1602	-9.0031

To shed light on the importance of allowing for stochastic volatility, Figures 2 and 3 plot the posterior means of the standard deviations of the errors in the three equations of the TVP-VAR for the US and Canada, respectively. For both countries, there is evidence of time variation, but the patterns are quite different. For Canada, the time variation reveals itself largely through a spike around 1997. For the longer US series, we see more peaks and troughs in the volatilities. Furthermore, a careful examination of the scale of the Y-axis indicates that it is only for the inflow hazard that substantial time variation in the error variance occurs. For Canada, Campolieti (2011) notes that there is a spike in the inflow hazard around 1997 and examines some other data sources for similar patterns. Campolieti (2011) concludes that the spike in the inflow hazard was likely related to changes in the LFS that occurred around this time, since the spike is not present in other data. More specifically, there was increased use of CATI interviews, changes in the survey questionnaire that added new variables and, most importantly, a change in the wording of the temporary layoff question that was phased in between September 1996 and January 1997 (Sunter et al, 1997) that would classify more individuals as unemployed. Campolieti (2011) also observes an increase in the Canadian outflow hazard around 1997. This increase in unemployment outflows is equivalent to a decrease in unemployment duration, which is also seen in Macklem and Barrillas (2005). However, as

Campolieti (2011) notes the reasons for this increase in the outflow rate from unemployment are unclear.

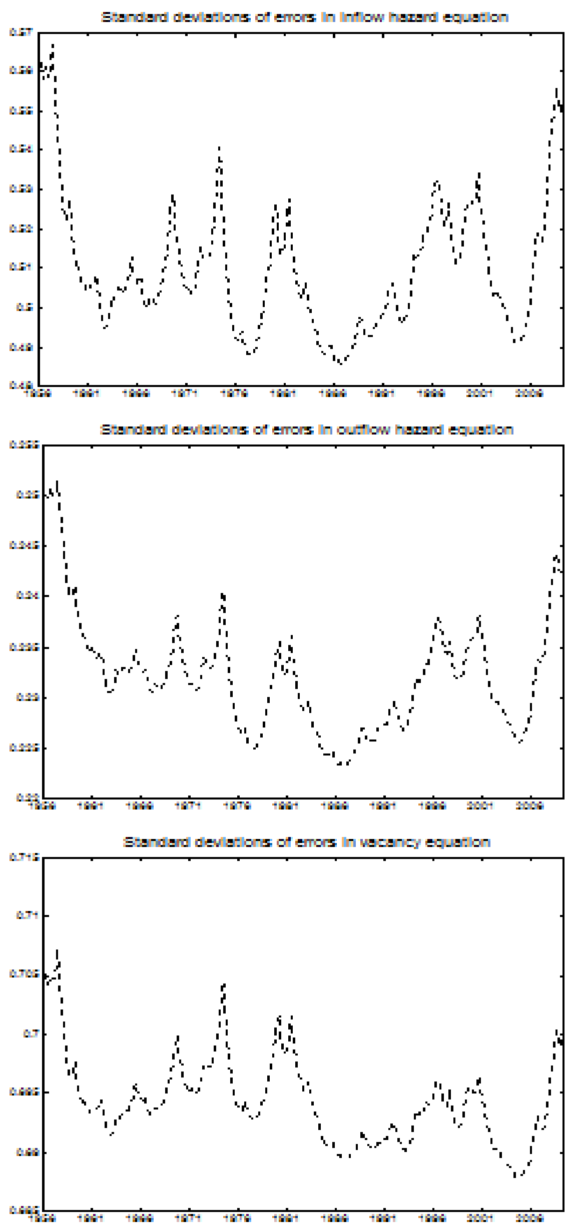

Figure 3. Standard Deviations -*Hete TVP-VAR*, US

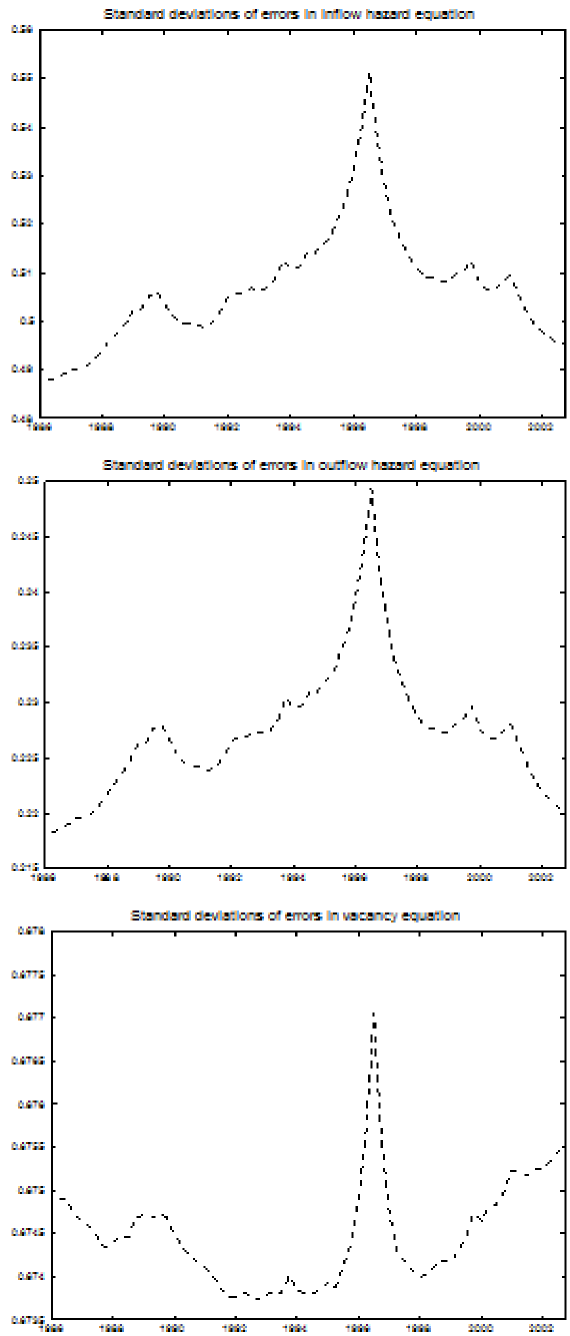

Figure 4. Standard Deviations -*Hete TVP-VAR*, Canada

3.3 Impulse Response Functions and Variance Decompositions

For each country, we calculate impulse responses and variance decompositions for various time periods. For the US, dates near business cycle troughs of 1982Q4, 1992Q3 and 2003Q2 are chosen as well dates near peaks of 1989Q2, 2000Q4. In addition, we use 2008Q2 to examine the effect of the recent crises. For Canada, troughs are 1982Q4, 1992Q4 and 2002Q1.[5] Peaks are around 1989Q3 and 2000Q2. We also include 2003Q1 as the last observation in the Canadian sample.

3.3.1 Variance Decompositions

Before presenting impulse responses, we provide information that the sign restrictions used to calculate them are reasonable ones. Tables 2 and 3 present a summary of the variance decompositions for the US and Canada, respectively (figures containing a full set of variance decompositions, including credible intervals, are available in the online appendix). The variance decompositions were calculated up to a horizon of 20 quarters. The tables present the average of the point estimate over all horizons. Tables 2 and 3 indicate that the aggregate shock we have identified accounts for an appreciable amount of the variability in all three of our variables. For the US, it account for roughly 40-45% of the variability in all three series. For Canada, comparable numbers are about 30-33%. These are similar to the figures presented in Fujita (2011) for his benchmark VAR.

[5] Canada did not enter a recession in the early-2000s, unlike the US.

Table 2: Average Variance Decomposition Rates for Hetero TVP-VAR, US

Time	Q4 1982	Q2 1989	Q3 1992	Q4 2000	Q2 2003	Q2 2008
Inflow Hazard	0.3888	0.3907	0.3914	0.4062	0.3950	0.4121
Outflow Hazard	0.4420	0.4429	0.4422	0.4394	0.4310	0.4376
Vacancies	0.4444	0.4393	0.4393	0.4414	0.4349	0.4422

Table 3: Average Variance Decomposition Rates for Hetero TVP-VAR, Canada

Time	Q3 1989	Q4 1992	Q2 2000	Q1 2002	Q1 2003
Inflow Hazard	0.3328	0.3206	0.3262	0.3281	0.3326
Outflow Hazard	0.3231	0.3102	0.3137	0.3164	0.3223
Vacancies	0.3289	0.3167	0.3234	0.3249	0.3249

3.3.2 Impulse Response Functions

Figures 5 through 8 present impulse responses for the US data with Figures 9 through 12 repeating the analysis for the Canadian data. All of these figures are responses to the aggregate shock identified using the sign restrictions. The four figures for each country are responses of four variables (inflow hazard, outflow hazard, unemployment rate and vacancy rate) to this shock at the time periods specified above. In all these figures the solid line is the posterior median and the dashed lines are the 16th and 84th percentiles of the posteriors. We present results only for the heteroskedastic TVP-VAR, but occasionally refer to results for other models. These latter results are available in the online appendix.

US Results

The response of the inflow hazard to the aggregate shock dies off steadily and fairly quickly (in about 8 quarters). In contrast, the outflow hazard, unemployment and vacancy variables exhibit hump-shaped patterns. These impulse responses tend to be near zero after about 3 or 4 years. These general patterns hold for every one of our time periods and also hold for the VAR and homoskedastic TVP-VAR.

The sign of the response for all the series we consider are unambiguous (i.e. they never flip from being positive at some horizons and negative at others), which provides support for the restrictions we use in the data. In other words, despite using weak restrictions we observe some features of the adjustment process in the US labor market quite clearly. The inflow hazard (separation rate) reaches its peak quickly and then declines slowly. The outflow hazard (job finding rate) and vacancies take a few quarters to reach the trough before starting to fade. The patterns in these series are like those in Fujita (2011). Moreover, they also support the conclusions in Elsby et al (2009) and Fujita and Ramey (2009) that unemployment dynamics in the US are driven by fluctuations in both the inflow and outflow hazard.

Overall, the differences across time periods do not appear to be too great. However, there are some variations over time and differences with standard VAR results which are worth noting.

For the inflow hazard, the impact impulse response found using the heteroskedastic TVP-VAR is larger than what is provided by the VAR. In addition, the impulse responses in 2000Q4 and 2008Q2 begin at a higher level and die away more steeply than for the other time periods.

For the outflow hazard, the point estimate for the impulse responses is similar in each time period, but the credible interval between the 16th and 84th percentiles becomes wider over time, with the 2008Q2 interval being very wide.

The wider credible interval in 2008Q2 is also found for the unemployment rate impulse response function. For this variable, the impulse responses exhibit the most variation over time. In particular, the responses to the negative aggregate shock in the peak years of 1989Q2 and 2000Q4 are smaller than in other years. In contrast, the impulse response function in the trough year of 1982Q4 is particularly large. And in 2008Q2 the effect of a shock takes much longer to die away.

For the vacancy rate, this pattern of wide credible interval in 2008Q2 and a tendency of the impulse response function to take a long time to move towards zero, is also found. Other than this, impulse responses for this variable are quite similar in each time period and similar to what is found for the standard VAR or homoskedastic TVP-VAR.

The time variation in impulse responses is most visible in the impulse responses for 2008Q2. Elsby et al (2010a) noted that there was an increase in the half-life of a deviation from steady state unemployment during the Great Recession relative to estimates of the half-life of a deviation from steady state unemployment obtained with data before the Great Recession (see also Elsby et al 2009; Elsby et al, 2010b). In addition, Elsby et al (2010a) also highlight that there was an overall slowdown in the rate of exit from unemployment during the Great Recession resulting in an accumulation of long-term unemployed persons. This accumulation of the long-term unemployed reduced the ability of the outflow hazard in the US to rebound. Our impulse response functions for the outflow hazard from 2008Q2 are consistent with these observations. More specifically, while the impulse responses for the outflow hazard for most of the periods we consider fade to zero, the impulse responses for 2008Q2 are still fairly large after 20 quarters. The impulse response for the inflow hazard 2008Q2 also tends to be larger than that for earlier periods and also takes longer to fade away. Elsby et al (2010a) also found some evidence of elevated levels of job loss, relative to earlier recessions, during the Great Recession. In particular, they found evidence of more separations due to layoffs during the Great Recession. Our impulse responses for 2008Q2 would be consistent with this changed pattern observed by Elsby et al (2010a).

The online appendix presents results for various priors and different choices for k and these are found to be of the same pattern as those presented here.

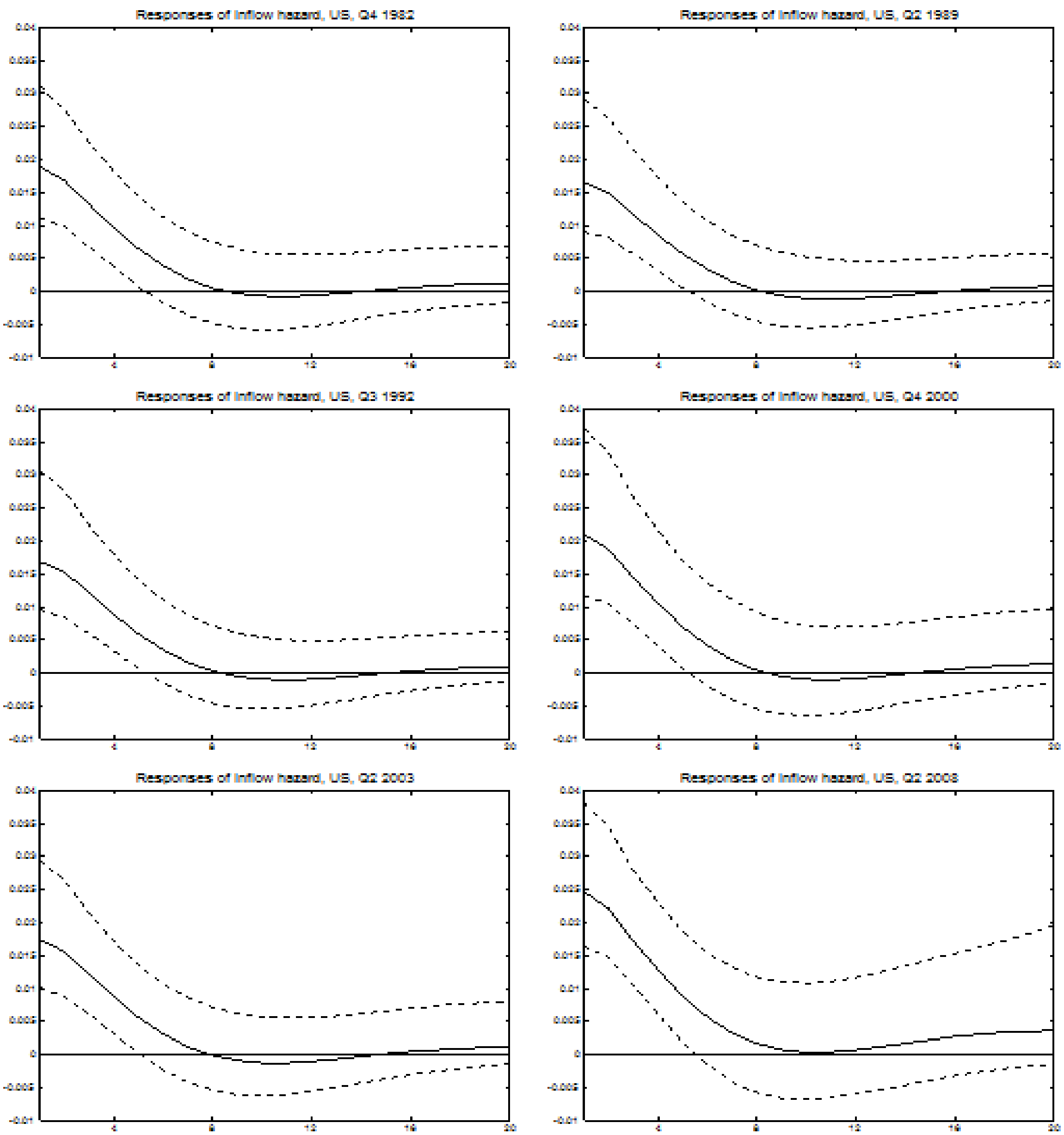

Figure 5. Impulse responses of inflow hazards -*Hete TVP-VAR*, US

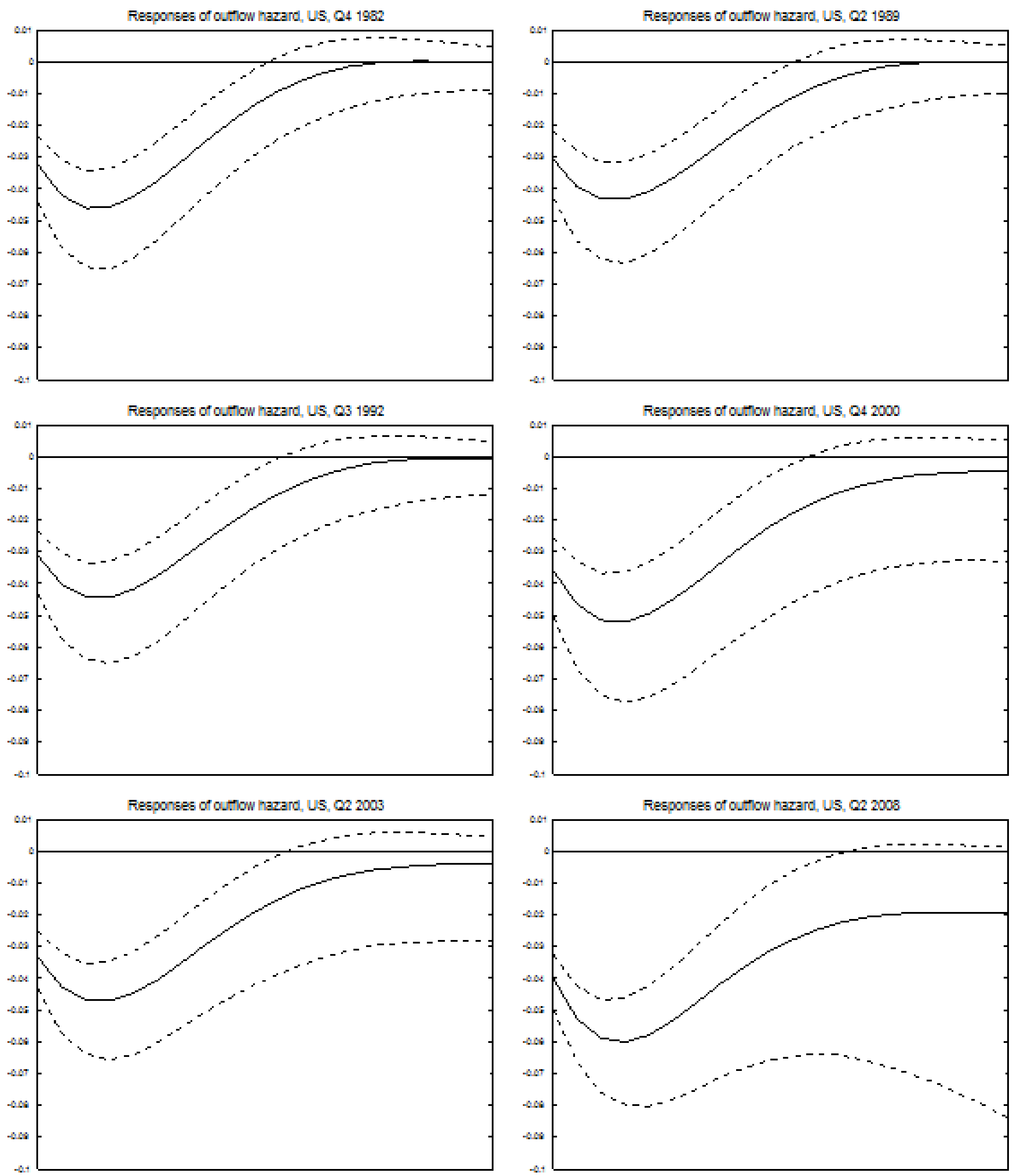

Figure 6. Impulse responses of outflow hazards -*Hete TVP-VAR*, US

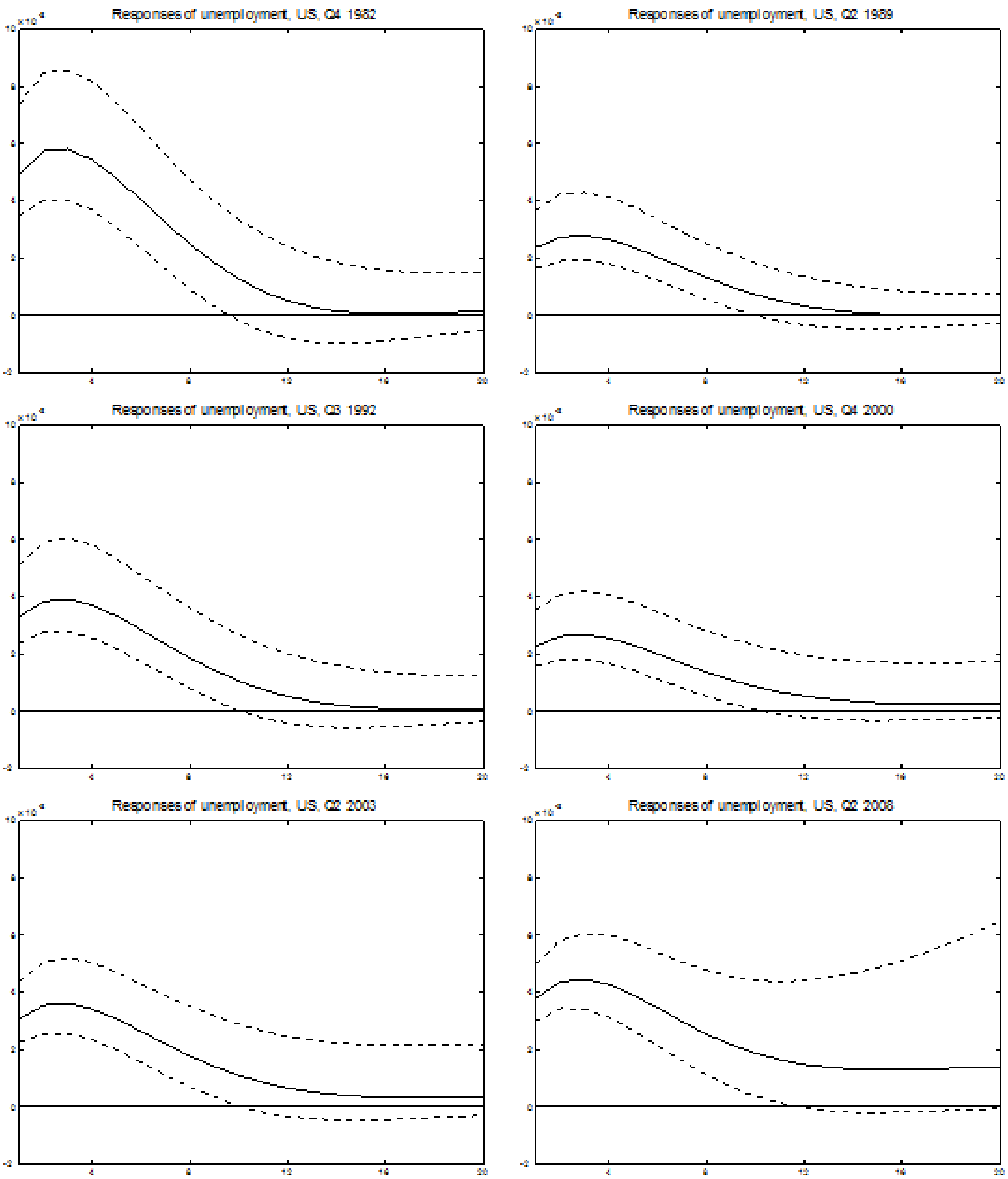

Figure 7. Impulse responses of unemployment -*Hete TVP-VAR*, US

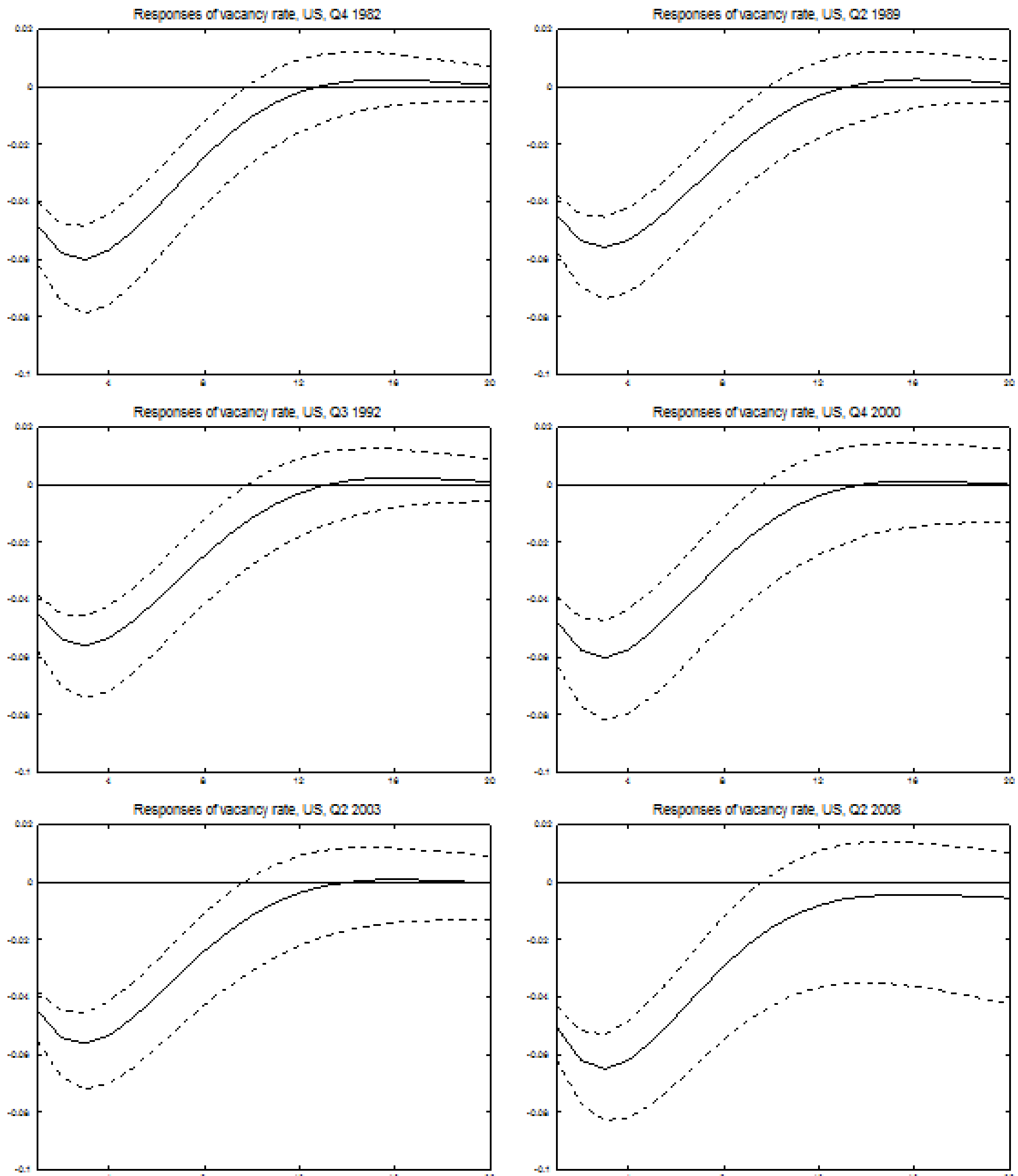

Figure 8. Impulse responses of vacancies -*Hete TVP-VAR*, US

Canadian Results

The general patterns found in the impulse responses using the Canadian data are somewhat different than US patterns. Impulse responses for the inflow hazard do indeed die off in a similar manner as we found for the US. But for the other variables, the hump-shaped US impulse responses are replaced by a more oscillatory response. The previous statement holds for the point estimates of the impulse response, although the credible intervals are fairly wide and include the hump-shaped pattern. The oscillation in the impulse response for the outflow hazard, relative to the US, is interesting in the context of the difference in unemployment rates that has existed between the two countries since the early-1980s (Riddell 2005). For most of the period we are considering the Canadian unemployment rate was higher than the US unemployment rate. The impulse responses for Canada, relative to the US, suggest that there could be lower exits from unemployment at longer horizons. This is consistent with the observations made in Campolieti (2010), who found that changes in the outflow hazard were responsible for a large part of the Canada-US unemployment rate gap.

In general, with Canadian data there is less evidence of time-variation in impulse responses. For the inflow and outflow hazards and the vacancy rate, there is little evidence of change over time in the impulse response functions. Although, for the inflow hazard, there is some weak evidence that the effect of the negative aggregate shock is getting weaker over time. That is, impact responses are slightly less in 2002Q1 and 2003Q1 than in earlier years.

The similarity of the impulse responses for the periods we consider is like the pattern we observe in the US, except for 2008Q2.[6] The Canadian estimates, like the US ones, suggest that response to a shock is similar across time and the business cycle. Also, like the US, the inflow (job separation rate) and outflow (job finding rate) hazards both play an important role in the adjustment of the

[6] Remember that our Canadian data ends in 2003Q1 so we are not able to investigate the Canadian experience in the Great Recession.

labor market.

However, for the unemployment rate, the impulse response in 1992Q4 is substantially different than other years. The impact and maximum responses are higher in this trough year than at other periods. While 1992Q4 is contained in the 1990-1992 recession, the period covered by the time horizon for the impulse responses corresponds to the period referred to as the 'The Great Canadian Slump' (Fortin 1996), which was a prolonged period of slow growth for the Canadian economy that extended into the mid-1990s following the end of the 1990-1992 recession.

Results using different values for k are similar those presented here. However, results using the VAR or homoskedastic TVP-VARs do differ from those presented here in some minor ways (e.g. the VAR results do not exhibit the same oscillatory responses noted above). Furthermore, results are more sensitive to prior than was found with the US data (although this is not unexpected due to the shorter data span). The reader is referred to the online appendix for full empirical results relating to these points.

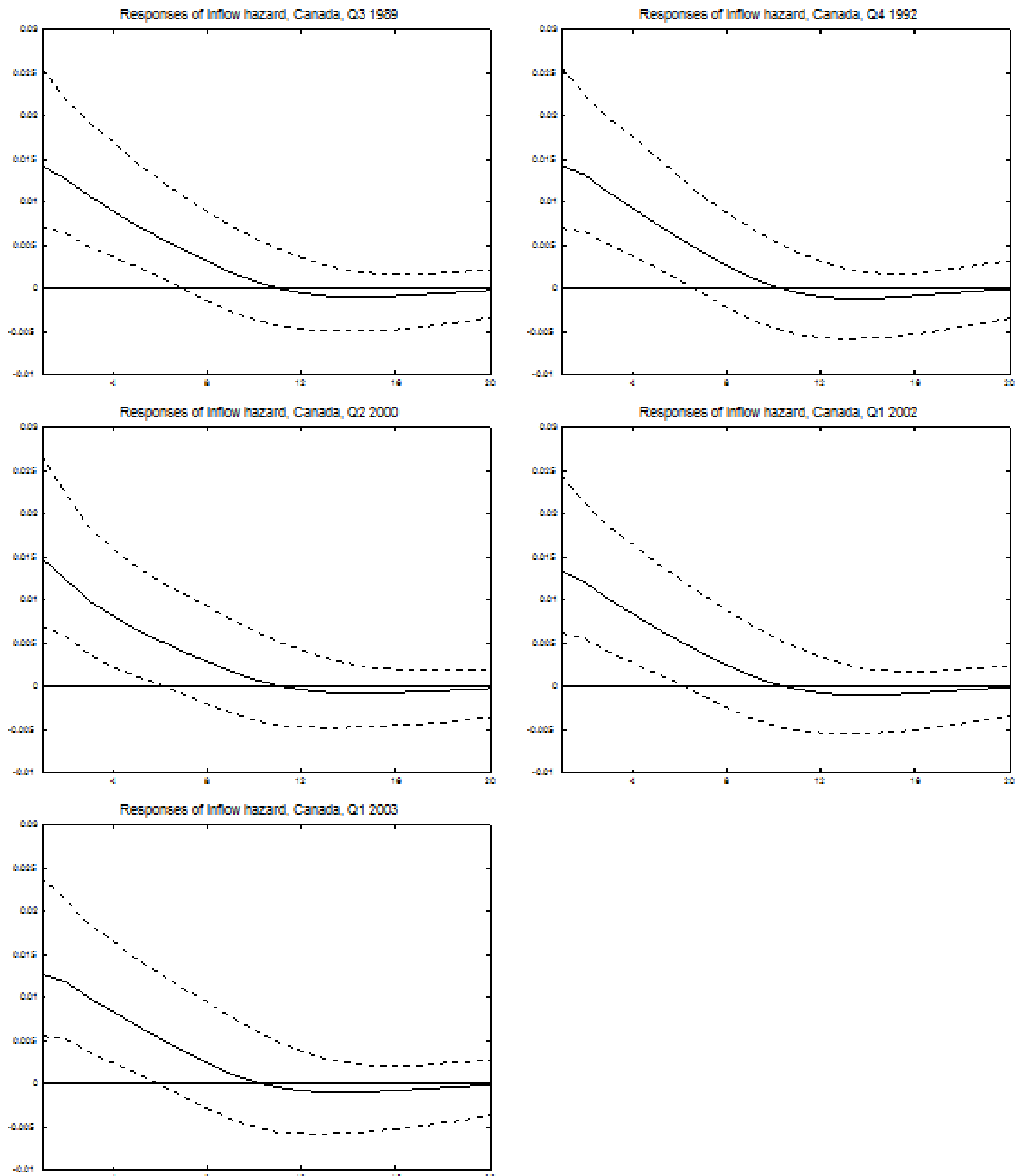

Figure 9. Impulse responses of inflow hazards -*Hete TVP-VAR*, Canada

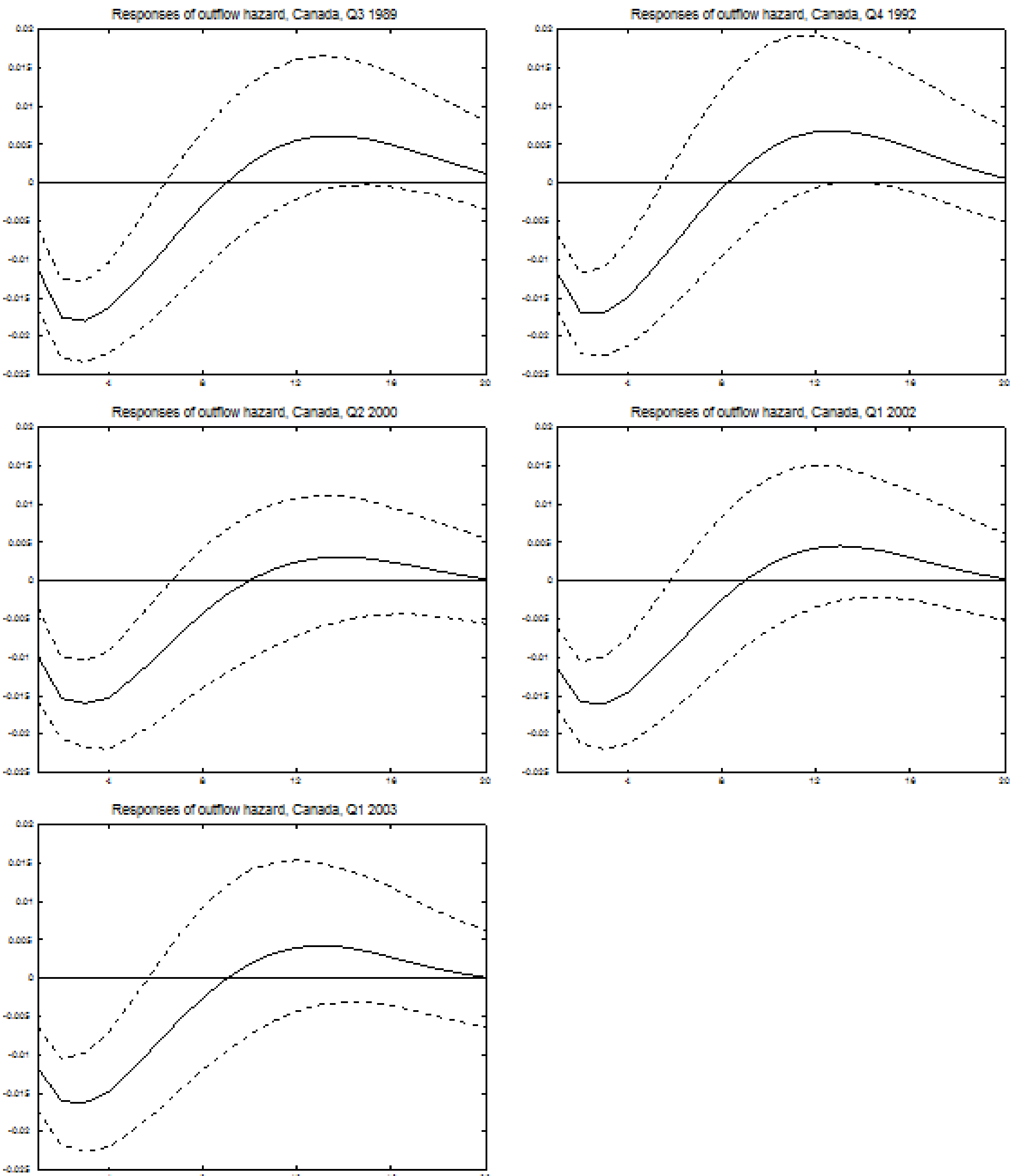

Figure 10. Impulse responses of outflow hazards -*Hete TVP-VAR*, Canada

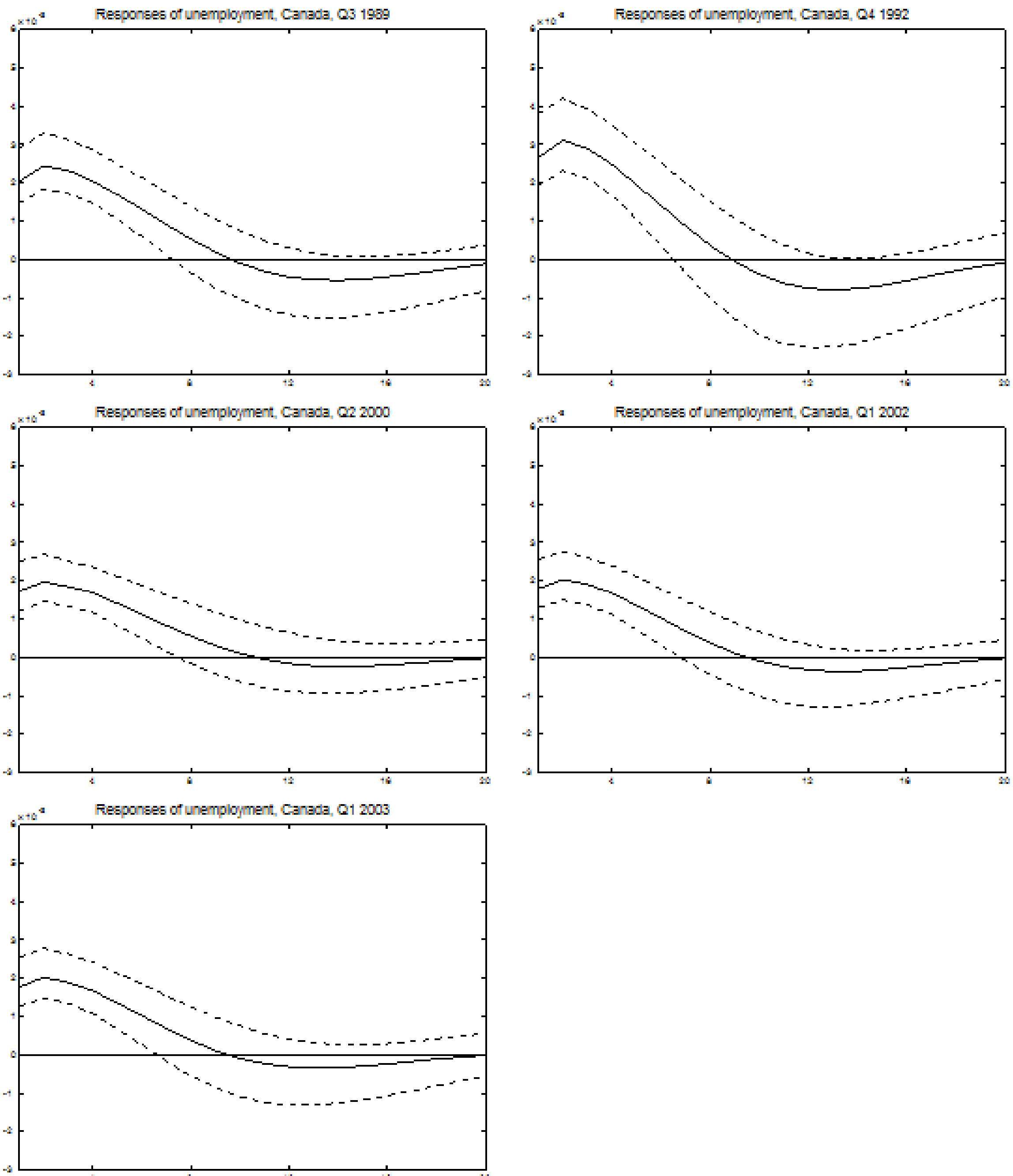

Figure 11. Impulse responses of unemployment rates -*Hete TVP-VAR*, Canada

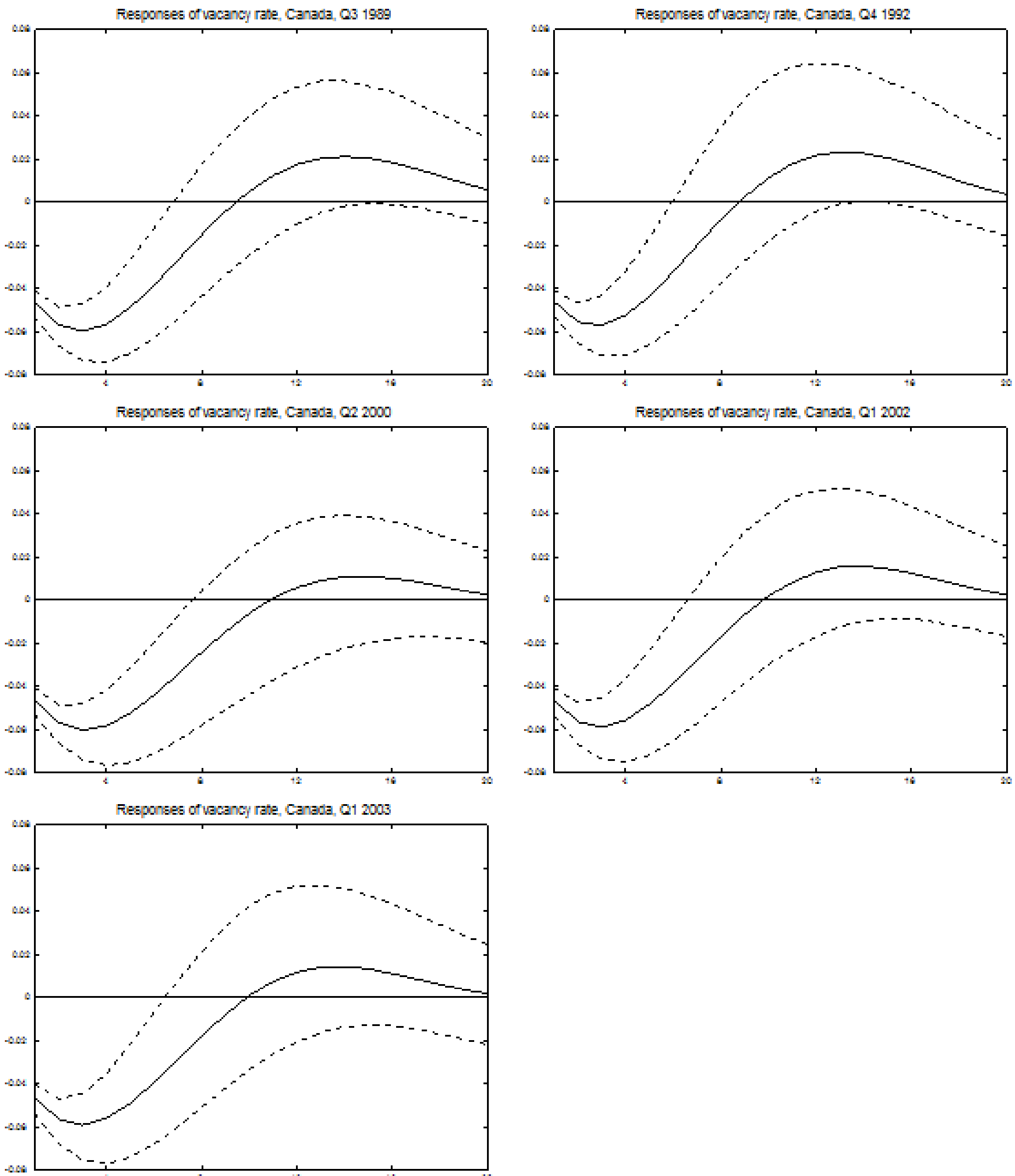

Figure 12. Impulse responses of vacancies -*Hete TVP-VAR*, Canada

4 Conclusions

In this paper, we have built on the existing literature which uses VAR methods for investigating the relationship between inflow and outflows into unemployment by using TVP-VAR methods. We also use both Canadian and US data. This allows us to see whether these relationships are changing over time. We find, particularly for the US, some interesting intertemporal changes. In particular, we find that responses of the inflow and outflow hazard during 2008Q2, which is during the US Great Recession, differ from those in the other periods we consider. More specifically, the inflow hazard (job separation rate) responds more strongly initially to a shock and takes longer to decay than the impulse responses for the other periods we consider. Likewise, the outflow hazard (job finding rate) also responds more strongly to a shock and does not decay as quickly or to the same level as the impulse responses for the other periods we consider. These findings suggest that unemployment dynamics and labour market adjustment during the US Great Recession differ from those in the other periods we consider. In contrast, the estimates from Canada indicate that the response to a shock does not vary a great deal over time or the business cycle and suggests that labor market adjustment occurs in a similar fashion during all the periods we consider in Canada.

Fujita (2011) concluded based on his findings from the VAR that models of the labor market should consider endogenous separations and the development of models that can replicate the hump shaped response in the outflow hazard and vacancies. Our results reinforce this conclusion.

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Technical Appendix

Bayesian Econometric Methods

In this section we provide additional details about our estimation of the VAR and heteroskedastic TVP-VAR. The homoskedastic TVP-VAR is the same as the heteroskedastic TVP-VAR except the treatment of its error covariance matrix model is the same as the VAR. Complete details on posterior inference in all those models is given in, among other places, Koop and Korobilis (2009).

The VAR given in (1) can be rewritten as:

$$Y = X\Theta + E$$

where $E = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_T)^{'}$ is the $T \times n$ matrix of error terms, $Y = (y_1, y_2, ..., y_T)^{'}$ is the $T \times n$ matrix of observations, X be a $T \times (np+1)$ matrix with t^{th} row containing an intercept and p lags of each of the n dependent variables. Θ is the matrix of VAR coefficients with $vec(\Theta) = \theta$.

In this model, with a noninformative prior, the posterior for H^{-1} is Wishart: $W(\widehat{H}^{-1}/T, T)$ with $E(H^{-1}) = \widehat{H}^{-1}$. The posterior for θ conditional on H is $N(\widehat{\theta}, H \otimes (X^{'}X)^{-1})$ where

$$\widehat{\Theta} = (X^{'}X)^{-1}X^{'}Y, \quad \widehat{H} = \frac{1}{T}(Y - X\widehat{\Theta})^{'}(Y - X\widehat{\Theta})$$

For the TVP-VAR defined by (2), (3), (5) and (6), MCMC methods are required. We use the same MCMC algorithm as Primiceri (2005) and the reader is referred to his paper for complete details. Briefly, conditional on all the other parameters, we draw from the posterior for θ_t (for $t = 1, .., T$) using standard Bayesian methods for state space models. We use the algorithm of Carter and Kohn (1994). The same algorithm is used to draw a_t. The algorithm of Kim, Shephard and Chib (1998), is used to draw the volatilities, $log(\sigma_t)$.

The covariance matrices of the errors in the state equations, Q, W and C are drawn from inverse-Wishart distributions (see Koop and Korobilis, 2009, Section 3.2 for precise formulae). As in Primiceri (2005), we assume C to be block diagonal with blocks C_1 and C_2.

We also using training sample priors as in Primiceri (2005) to initialize the states in the state equations and provide priors for Q, W and C. In particular, OLS estimates from a constant coefficient VAR using an initial training sample of size τ are used to calibrate the prior. Let $\widehat{\theta}_{OLS}$ and $V(\widehat{\theta}_{OLS})$ be the OLS estimate and its covariance matrix for the VAR coefficients. Similarly, the OLS estimate of the error covariance matrix can be decomposed as in (6) to provide us with $\widehat{\sigma}_{OLS}$, $\widehat{A}_{OLS}$ and $V(\widehat{A}_{OLS})$. Primiceri (2005) uses the following prior

$$\theta_0 \sim N(\widehat{\theta}_{OLS}, 4.V(\widehat{\theta}_{OLS}))$$

$$A_0 \sim N(\widehat{A}_{OLS}, 4.V(\widehat{A}_{OLS}))$$

$$log\,(\sigma_0) \sim N(log\,(\widehat{\sigma}_0)\,, I_3)$$

$$Q \sim IW(k_Q^2 \tau V(\widehat{\theta}_{OLS}), \tau)$$

$$W \sim IW(4k_W^2 I_3, 4)$$

$$C_1 \sim IW(2k_C^2 V(\widehat{A}_{1,OLS}), 2)$$

$$C_2 \sim IW(3k_C^2 V(\widehat{A}_{2,OLS}), 3)$$

where $\widehat{A}_{1,OLS}$ and $\widehat{A}_{2,OLS}$ are the blocks of $\widehat{A}_{OLS}$ corresponding to the blocking of C into C_1 and C_2. With this setup, the complicated prior elicitation procedure for the high-dimensional TVP-VAR is reduced to the choice of τ and the scalars k_Q, k_C and k_W. Following Primceri (2005), the main results in our paper set these scalars to be 0.01, 0.1 and 0.01, respectively. For the training sample, we use the initial 5 years of data, $\tau = 20$. In a prior sensitivity analysis, available in the online appendix, we investigate the sensitivity of the prior to these choices. For the homoskedastic TVP-VAR, we require a prior for H. Given the scale of the data the following choice is centered in a sensible region, but is relatively noninformative:

$$H \sim IW(\widehat{H}_0, 4).$$

where $\widehat{H}_0$ is the OLS estimate of the error covariance matrix using the training sample.

Impulse Response Analysis Using Sign Restrictions

To estimate the impulse responses, we extend the sign restriction approach of Uhlig (2005) which was developed for the VAR to the TVP-VAR framework. Basically, the approach of Uhlig (2005) involves repeatedly simulating impulse responses from the VAR, but omitting draws which violate the sign restrictions. With the TVP-VAR we implement this approach by calculating sign-restricted impulse responses at time t using the VAR coefficients and VAR error covariance matrix which hold at time t (i.e. θ_t and H_t). With the TVP-VAR the impulse response simulation must be done within a posterior simulation algorithm which can be computationally costly. Accordingly, we calculate sign restricted impulse responses at a few selected time periods, rather than for all t. Precise details are provided in the remainder of this section.

Suppose that ω_t is an $n \times 1$ vector of mutually independent structural innovations with $E(\omega_t \omega_t^{'}) = I_n$. The relationship between ε_t and ω_t can be written as $\varepsilon_t = G_t \omega_t$, with the only restriction that $G_t G_t^{'} = H_t$. Thus, if $\omega_{t+1} = e_j$, with e_j be an $n \times 1$ vector with zeros everywhere except for the j^{th} entry equal 1, we have $\varepsilon_{t+1} = G_t e_j = g_{t,j}$, with $g_{t,j}$ be the j^{th} column of G_t. Similarly, we can compute $r^h_{e_j,o,t}$, the impact responses of variable o at horizon h to a shock

e_j, as $r^h_{e_j,o,t} = (\Gamma^h_t \mathbf{g}_{j,t})_o$, where $\mathbf{g}_{j,t} = (g^{'}_{j,t}, 0_{1,p(l-1)})'$, and

$$\Gamma_t = \begin{pmatrix} B_{1,t} & B_{2,t} & ... & B_{l-1,t} & B_{l,t} \\ I_n & 0 & ... & 0 & 0 \\ 0 & I_n & ... & 0 & 0 \\ ... & & ... & & ... \\ 0 & 0 & ... & I_n & 0 \end{pmatrix}$$

with the $n \times n$ matrix $B_{i,t}$, whose elements are contained in θ_t, being the parameter matrix corresponding to the i^{th} lagged dependent variables in the TVP-VARs.

Following Uhlig (2005), we decompose H_t into $G_t = X_t \Lambda_t^{\frac{1}{2}} F_t$, where X_t is an $n \times n$ orthogonal matrix whose columns are the orthonormal eigenvectors of H_t, $\Lambda_t = diag(\lambda_{1,t}, \lambda_{2,t}, ..., \lambda_{n,t})$ is the corresponding eigenvalues matrix of Σ_t, and F_t is an $n \times n$ orthogonal matrix (i.e., $F_t F_t^{'} = I_n$). Then an impulse vector g_t can be constructed as following:

$$g_t = X_t \Lambda_t^{\frac{1}{2}} f_t \tag{7}$$

where f_t is an orthonormal vector uniformly drawn from a unit sphere. Let $\mathbf{g}_t = (g^{'}_t, 0_{1,p(l-1)})^{'}$, with l being the lag length of the TVP-VARs. We can calculate the impact responses of variable o at horizon h to a shock at time t as $r^h_{o,t} = (\Gamma^h_t \mathbf{g}_t)_k$. By repeatedly generating a large number of g_t and imposing a set of inequality constraints on r^h_o, the impulse responses are obtained.

The sign restriction approach is incorporated in our TVP-VAR MCMC algorithm. We generate 1000 impulse response vectors, g_t, at each MCMC draw. The posteriors for our impulse responses are based only on those draws that meet the sign restrictions.